An Empirical Study of Translation Hypothesis Ensembling with Large Language Models

António Farinhas^{1,2}, José G. C. de Souza³, André F. T. Martins^{1,2,3}

¹Instituto Superior Técnico (Lisbon ELLIS Unit), ²Instituto de Telecomunicações, ³Unbabel

There's lots of research on task-specific NMT models but LLMs offer a new perspective!

We generate multiple hypotheses by using a single prompt and sampling multiple times; we ensemble them using different techniques.

Translation Hypothesis Ensembling

Using external quality estimation/evaluation models

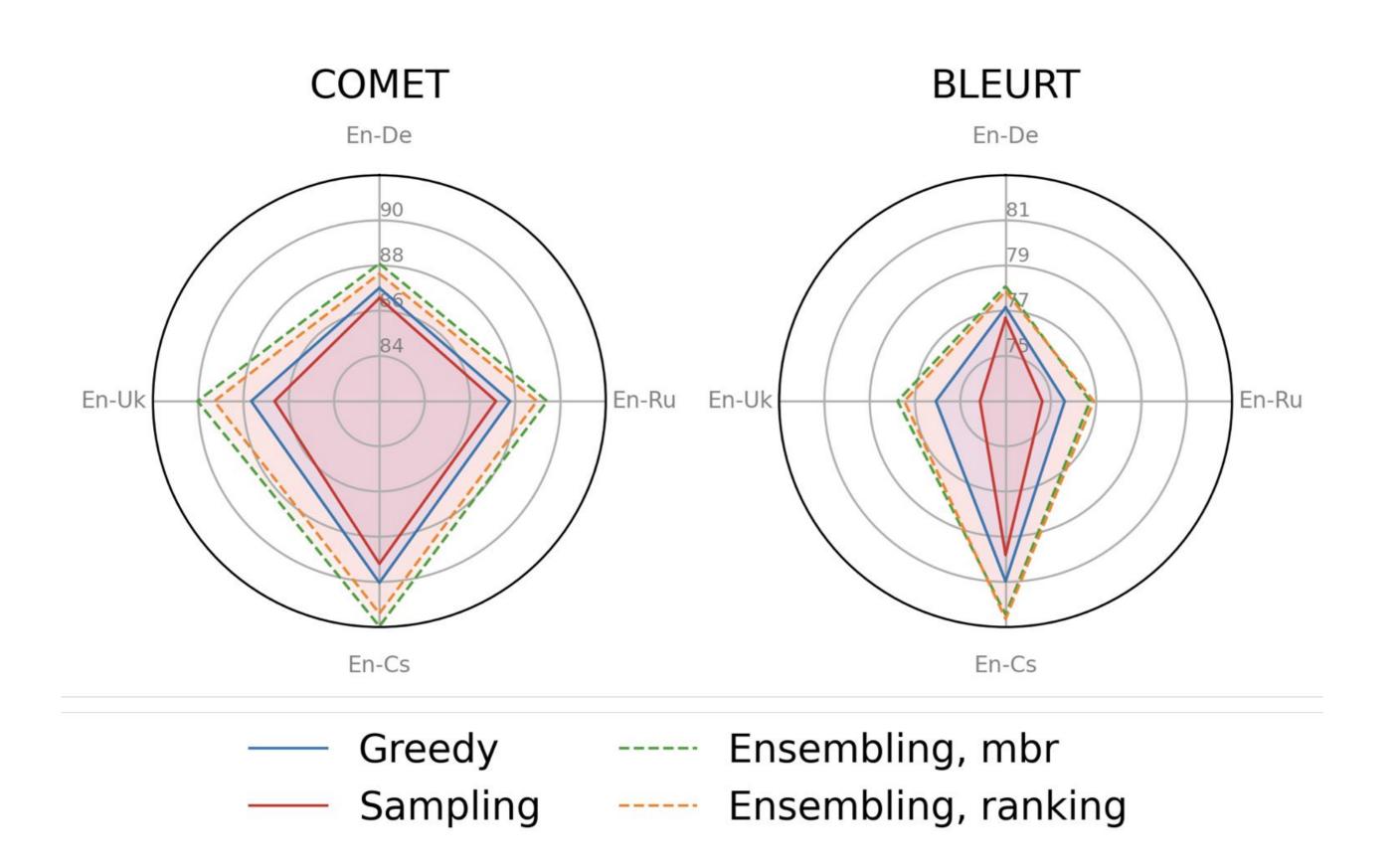
- ranking with QE: $\hat{y}_{\text{ranking}} = \operatorname{argmax}_{y \in \bar{\mathcal{Y}}} \operatorname{CometKiwi}(y)$
- ullet MBR decoding: $\hat{y}_{\mathrm{mbr}} = \mathrm{argmax}_{y \in \bar{\mathcal{Y}}} \, \mathbb{E}_{Y \sim p_{ heta}}[\mathrm{COMET}(Y,y)]$

Using the LLM

- ChooseBest: formulated as a multiple choice question
- GenerateBest: asking the LLM to generate a final prediction

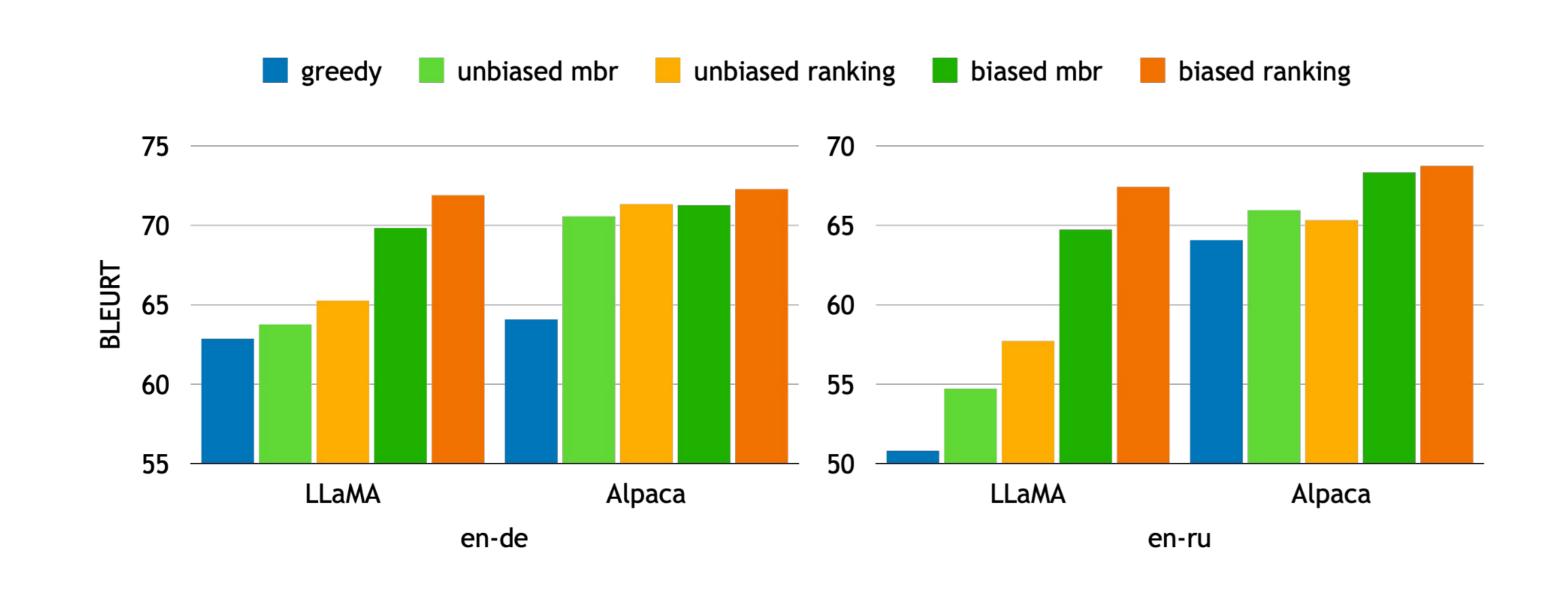
ChatGPT

 translation quality can be enhanced with a small number of unbiased samples, especially for EN-X

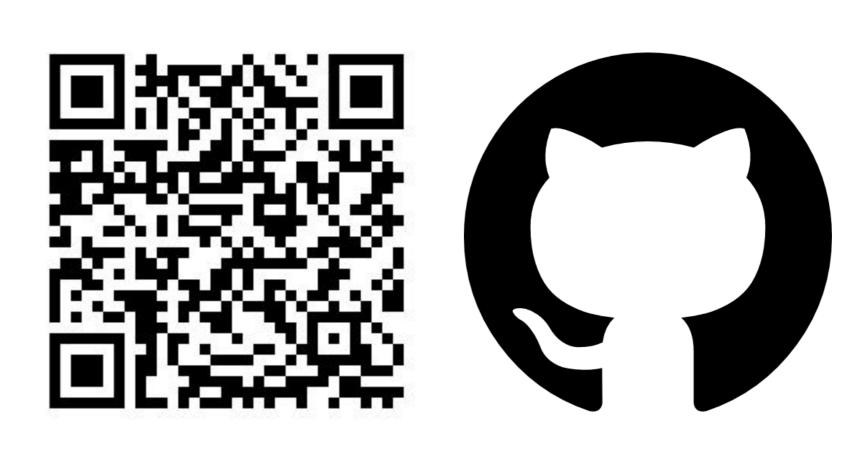


LLaMA and Alpaca

- ensembles of unbiased samples from LLaMA don't perform well
- alpaca performs better and biasing samples boosts performance

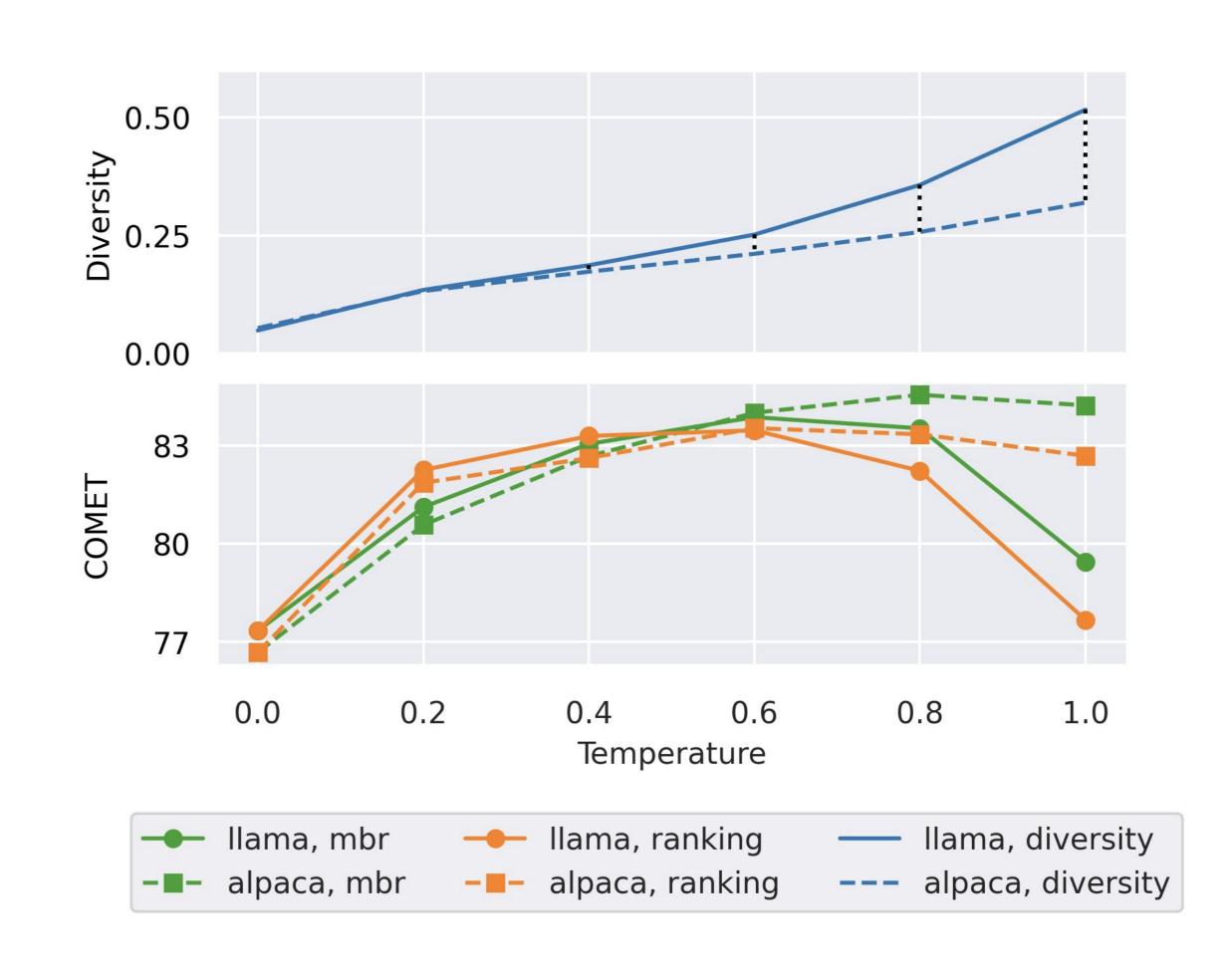


Check the paper for more LPs and analysis!



Biasedness, diversity, and

• the diversity between hypotheses increases with the sampling temperature at a different rate for LLaMA and Alpaca



Hallucinations

- hallucination rate decreases with instruction tuning
- ensembling translations decreases the number of hallucinations

